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Structural Change and Tests of Market Power in the US Food Industry

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by

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Abstract

This study outlines a theoretical model and empirical approach to the estimation of market clearing models and tests of market power. We also develop our approach on conjunction with a discussion of the empirical content and econometric approach to data undergoing structural change. We argue that structural change implies data non-stationarity and therefore that a cointegration approach to estimation and testing is needed to make inference of market power in the US food industry. We develop an extensive set of market power tests that are both parametric cross equation restriction tests and non-parametric single equation specification and cointegration tests. Tests are then implied to seven US food industries. While the results are mixed, our tests do tend to find a larger degree of competition within aggregate US food industries than previous studies. Even for those tests that are rejected, test restrictions and results are based on asymptotic results that are probably be biased against the null of competitive markets for small samples.

1.0 Introduction:

Concern over a small number of firms exerting undue influence in price setting and output decisions has existed at least since Adam Smith. Indeed, Smith himself, that champion of competitive forces and enlightened self interest, was no lover of business people, who he regarded with suspicion as those who conspired to circumvent the natural tendencies of market forces.

The rise of modern capitalism during the last three centuries has not dampened the suspicions of market observers, indeed, concerns over what were considered to be anti-competitive behavior within the economy has given rise to the whole structure, conduct and performance paradigm within the economics profession. The increasing concentration of the economics profession on game theoretic approaches to the study of markets has at least in part been driven by dissatisfaction with perfect competition in explaining a large number of industries in the economy.

Within agriculture, the presumed market power of a small number of firms within the marketplace has been used to justify a whole host of agricultural policies designed to give primary agricultural producers countervailing power vis a vis large marketing and processing firms within the agri-food marketing chain. Alarm over growing market power often comes in response to rising farm to retail price spreads. The presumed regularity of increasing price spreads over time coupled with increasing concentration ratios is most often taken as empirical verification of the existence of an increase in market power.

Of course, the problem with using increasing price spreads or increasing concentration ratios as evidence in favor of market power is that neither taken separately nor together implies the existence of market power. Furthermore, the casual empiricism and anecdotal nature implied by the documentation of the temporal movements of concentration ratios and price spreads can hardly be described as a test for market power within an industry as such tests are defined in the economics literature. Because of these deficiencies, there is a growing literature devoted to the development of more powerful theoretical models that can lead to empirical tests for market power using statistical procedures. In this study, we provide a theoretical framework and empirical framework that can be used to test for market power that is more up-to-date than methods used previously in the literature.

One critique of the literature that utilizes theoretical models and statistical techniques to test for market power rests on the argument that Astructural change≅ in a market renders either the theoretical model or the statistical techniques invalid. AStructural change≅ is often used as an argument that the commodity is Adifferent≅ at the consumer level, or that the market has Achanged≅ in a manner that makes the theoretical model either suspect or irrelevant.

A serious drawback of the Astructural change≅ critique is that analysts seldom if ever define precisely what is meant by Astructural change≅ in a market. Presumably, it is not the existence of Astructural change≅ per se that causes problems with theoretical models and empirical tests but that the markets cannot respond to such changes in a manner that is consistent market structures that existed in the past or that Astructural change≅ is not consistent with the historical data generating process making empirical tests invalid.

An alternative explanation of Astructural change≅ is that it is really just trends and shocks in the data emanating either from either demand or supply sides of the market. If such trends are adequately past from demand to supply or vice versa, then a stable market structure is able to respond to Astructural change≅ without invalidating either theoretical models or empirical tests.

In this paper, we take a different approach designed to augment the theoretical development of the literature. Our concern is not to develop new theoretical models with which to test for market power, but to concentrate of the time series properties of the data used for these tests. In particular, we argue that the data used to test for market power are non-stationary in nature, including both stochastic and deterministic trends. Understanding the nature of these trends is fundamental both to the understanding of the market forces driving agricultural industries as well the selection of appropriate econometric techniques to test for market power. Indeed, the existence of stochastic trends in agricultural markets can explain the tendency for industries to become more concentrated over time without recourse to increasing market power arguments. The lack of appreciation for the time series properties of the data is a major drawback of previous attempts to test for market power in the food marketing chain.

In this study, we develop tests for market power that are consistent with the time series properties of the data. Using a wide variety of food commodities, we do not find a significant degree of market power within most commodity groups studied for US agriculture and conclude that previous attempts to test for market are probably spurious in nature and are biased away from the competitive conclusions.

This study is organized into four sections including this introduction. In the next section, a model of farm to retail price spreads developed by Wohlgenant and Wohlgenant and Haidacher is presented. While not new, this model is presented so that it can be analyzed from the standpoint of time series non-stationarity. That is, Wohlgenant=s model provides the empirical basis for testing for market power as well as interpreting stochastic and deterministic trends in the data as well as an alternative to the more restrictive interpretation of the data coming from, say, constant markup or input/output models of marketing margins. Following the theoretical section, a section on the interpretation of the interpretation of the intertemporal movements of food price spreads will be given. The next section will present the statistical results of this study, while the final section concludes.

2.0 Theory

Wohlgenant (1989) and WH introduced the agricultural economics profession to a market-clearing framework in which diverse firms demand farm and nonfarm inputs to produce the product mix of a composite industry. By relaxing the restriction of identical production functions across firms, they account for an industry's heterogeneous food items. They note that even if *each* firm produces its items in fixed-input proportions, because proportions vary across the diverse firms of a food industry, production of the entire industry is variable proportions.[1] The framework equips analysts with a tool for studying market relationships that is more general than the models derived from the traditional assumptions of fixed proportions and identical firms.

Market models of diverse firms generalize competitive market relationships. In particular, they can be used to reconcile the *concept* of competitive markets with the *observation* that: 1) increases in consumer food prices are not fully passed through to farmers (Wohlgenant, 1994); 2) nonfarm input prices and consumer food prices may move in opposite directions; 3) consumers may pay higher markups for higher priced products (George and King); and 4) competitive food industries may earn positive longrun rents (U.S. Department of Agriculture, September 1996). Market models based on fixed-proportions production must appeal to imperfect competition to explain these observations (Wohlgenant, 1999).

Tests of market power using market-level data, then, depend on assumptions concerning the nature of *industry* production. Retail-to-farm price spreads that exceed the marginal cost of transforming farm ingredients to final food products suggest market power, but the formulas used to compute spreads depend on the industry production function.[2] Studies based on fixed-proportions consistently reject the competitive model (e.g., Schroeter, Schroeter and Azzam, Azzam, Azzam and Park, and Koontz, Garcia, and Hudson), whereas WH and Wohlgenant (1989, 1996) just as consistently fail to reject the competitive model for U.S. food industries.[3]

This section presents an overview of the theory used in our empirical analyses. We refer readers unfamiliar with this theory to the cited studies of WH and Wohlgenant (1989, 1996) for a discussion that is more complete than that presented in this section. Readers familiar with the theory can skip to the next section.

At the core of the WH model are a pair of quasi-reduced-form retail and farm price equations for each market and a system of consumer-demand relationships linking the markets. Given a consumer demand schedule, the underlying structural model consists of two market-clearing conditions. The first states that the sum of food supply across the firms of the industry equals consumer demand for the industry output. The second states that the sum of farm ingredient demand across firms of the industry equals farm supply. *The critical feature of the WH model is that an industry's firms are not restricted to possessing identical production functions.* Within this general setup, WH assume that each industry faces an infinitely elastic supply of nonfarm inputs (exogenous nonfarm input prices), and a less-than-infinitely elastic supply of farm ingredients (endogenous farm prices). To simplify the model structure and isolate analysis on retail and farm prices, WH assume the food industry for a particular market consists of all the firms that manufacture, wholesale, and retail the industry's final food products.

Based on this structure[4] and on market clearing for farm ingredients and food output, Wohlgenant (1989, 1996) and WH derive the quasi-reduced-form

$$
(1) \qquad \begin{aligned} lnP_{rj} &= A_{rf}^{(j)}\, lnF_j + \boldsymbol{A_{rw}^{(j)}}\, \boldsymbol{lnW} + A_{rz}^{(j)}\, lnZ_j + \varepsilon_{rj} \\ lnP_{fj} &= A_{ff}^{(j)}\, lnF_j + \boldsymbol{A_{fw}^{(j)}}\, \boldsymbol{lnW} + A_{fz}^{(j)}\, lnZ_j + \varepsilon_{fj} \end{aligned} \qquad j = 1,\ldots,J
$$

in which lnP_{rj} represents the natural logarithm (log) of the retail price in the jth market, lnP_{fj} is the log of the price of the farm ingredient used to produce output of the jth market, lnF_j is the log of the supply of the farm ingredient used to produce output of the jth market. In this study, lnF_j captures changes in domestic supply, and excludes changes in net exports and changes in private and government stocks of farm commodities. $\boldsymbol{lnW}$ is a vector of logged nonfarm input prices and lnZ_j is a consumer demand shifter to be defined below. ε_{rj} and ε_{fj} are model errors on the retail and farm price equations.[5] These two retail and farm price equations are central to this bulletin.

In this framework, consumer demand defines the market, and the total consumer demand shift variable for the jth market, lnZ_j, represents the effect of all variables that affect demand except the own-retail price for the product. For this bulletin, lnZ_j is derived as follows. Let

$$
ln(Q_j /POP) = e_{jj}\, lnP_{rj} + e_{jy}\, ln\,(Y/POP) + \sum_{k \neq j} e_{jk}\, lnP_{rk} + u_j
$$

be a per capita consumer demand relationship for the jth product in which $ln(Q_j/POP)$ is the log of per capita consumer demand for the output of the jth industry, lnP_{rj} is the log of the own-retail price, $ln(Y/POP)$ is the log of per capita disposable income, lnP_{rk} $(k \neq j)$ is the kth retail price of a gross substitute or complement to product category j, and u_j is an error term. Hence, the e_{jj} is the own-retail price elasticity of consumer demand, e_{jk} $(k \neq j)$ is a set of cross-price elasticities of demand, and e_{jy} is the income elasticity of demand for the jth good. Based on this relationship, the total demand shifter for the jth market is

(2) $$lnZ_j = e_{jy}\ ln\ (Y/POP) + \ni_{k\ \ j}\, e_{jk}\ \ lnP_{rk} + lnPOP$$

in which *lnPOP* is the log of population. lnZ_j does not capture shifts in consumer demand caused by changes in the demand for food away from home, nor does it capture shifts caused by changes in the composition of the population.

The equations *1* are “quasi” reduced because they account for market-clearing in the *j*th market independent of market clearing in other markets.[6] Theory suggests four sets of expected signs on the quasi-reduced forms.

First, Heiner proves that for an industry of diverse firms, an increase (decrease) in the price of an input decreases (increases) an industry’s demand for the input. While this result is standard for an isolated firm and for an industry comprised of identical firms, Heiner=s proof applies to an industry comprised of firms with different longrun average costs. Heiner’s proof does *not* describe the negative slope of the sum of competitive firms’ input demand schedules holding output price constant. It describes instead the slope of industry input demand schedule as the sum of firms’ supply moves along a downward-sloping consumer demand schedule and output price changes.[7] Braulke showed that Heiner’s proof applies to longrun equilibrium in which firms enter and exit the industry. In equations 1, $A_{ff}^{(j)}$ is the own-price flexibility of an industry’s demand for farm ingredients, and theory suggests $A_{ff} < 0$.[8]

Second, the industry’s longrun quantity of food supply increases with its own-consumer food price. Heiner, Braulke, Panzar and Willig, and WH show that even if all input prices are exogenous to a competitive industry (flat input supplies), firm diversity implies that positive shifts in consumer demand trace an upward-sloping longrun industry supply function. Theory implies $A_{rz} > 0$.

Third, if firms are identical and farm ingredients are *normal* factors of production, a decrease in the supply of farm ingredients leads to a contraction of food supply and to an increase in consumer food prices. A *normal* factor of *industry* production is one in which the industry uses more of the factor to produce more output, while an inferior factor is one in which the industry uses less of the input to produce more output. The theory of diverse firms extends the neoclassical result that an increase in farm prices leads to increases in food prices only if farm ingredients are normal factors of industry food production. Since we expect that the aggregate farm ingredients specified here are normal, we expect $A_{rf} < 0$.

Fourth, if farm ingredients are normal factors of industry production and firms are diverse, positive shifts in consumer demand lead to long run increases in farm prices. For that reason we expect $A_{fz} > 0$.

The theory of diverse firms does not unambiguously sign the response of consumer food prices to changes in nonfarm input prices. The reason is that a marketing input may be an *inferior* factor of production.[9] An increase in the price of an *inferior* factor raises a firm's average costs, but *reduces* its marginal costs. For a competitive industry comprised of identical firms, higher longrun average costs drive firms from the industry, reduce industry supply, and drive up consumer prices. The results may be different if an industry's firms are diverse.

Inframarginal firms are bestowed with firm-specific fixed assets that earn rent in the long run. Such firms are bestowed with firm-specific entrepreneurial capacity (Friedman) or location that provides them with a cost advantage over marginal firms (Panzar and Willig). One could argue that the entrepreneurial capacity of inframarginal pork-producing firms in the Southeast United States exceeds that of marginal producers in the Midwest. The cost advantage of inframarginal firms allows them to remain in the industry even as the long run average cost of other firms is above market price. It follows that even in competitive markets, if the factor is inferior to inframarginal firms, an increase in its prices allows inframarginal firms to increase their supply even in the long run. The increase places downward pressure on output price. On the other hand, if the factor is inferior to marginal firms, their long-run average cost rises above output price. Marginal firms would exit the industry, thereby reducing industry supply and placing upward pressure on the market's average price of output. A negative sign on an element of $\boldsymbol{A}_{rw}$ suggests the associated factor is inferior to *industry* production, and that the positive supply response of inframarginal firms outweighs the negative response of marginal firms[10] (Panzar and Willig).

Theory provides a homogeneity condition. Since consumer demand is homogeneous of degree zero in retail (food) prices and income, and output supply and input demand are homogeneous of degree zero in farm and nonfarm input prices, the market-clearing price equations of (1) are homogeneous of degree zero in farm and nonfarm input prices, retail prices, and income (e.g., WH, Wohlgenant [1989], Chavas and Cox).

The WH framework provides a test of the competitive model. The test is based on the notion that if a firm is a price taker in both its purchase of inputs and its sales of output its profit function exists, and the symmetric second derivatives of its profit function define reciprocal relationships between a firm's output supply and input demands. Wohlgenant and WH derive an analogous symmetry condition for the group of diverse industry firms. Denoting $S_f^{(j)}$ as the cost share of farm ingredients for the *j*th industry, and to the coefficients in (1), WH show that symmetry at the *industry* level implies

$$A_{rf}^{(j)} = -S_f^{(j)} A_{fz}^{(j)}.$$

This condition states that if firms take farm and consumer prices as given, there exists a symmetric response of consumer and farm-level prices.

When studying retail and farm price relationships, analysts are often interested in the elasticity of transmission of farm prices to retail food prices. The *elasticity of price transmission* is the percent change in a retail food price induced by a 1-percent change in the farm price (George and King). Estimates of this elasticity reduce to the farm share if the food industry is competitive and if industry production exhibits constant returns with respect to farm ingredients. The assumption of fixed-proportions production (at the industry level) imposes constant returns with respect to *all* inputs, and therefore ensures transmission elasticities equal to the farm share. The WH model allows us to test whether the elasticity of price transmission equals the farm share within a variable-proportions framework.

Wohlgenant and WH show that in terms of the coefficients of (1), the jth industry's production displays constant returns with respect to the farm input if

$$A_{rz}^{(j)} = -A_{rf}^{(j)}$$

$$A_{fz}^{(j)} = -A_{ff}^{(j)}$$

hold. Constant returns for an industry imply zero industry profits in the long run. If both the symmetry and the constant returns restrictions hold, the elasticity of price transmission equals the farm share.

The model provides refutable hypotheses concerning oligopsony power. Policy makers often express concern that food producers exert market power when acquiring raw agricultural commodities from farmers. Some point out that captive supplies associated with new marketing arrangements may have changed the market structure so as to favor food producers and keep farm prices below competitive levels (U.S. Department of Agriculture, February 1996). Others counter that such voluntary arrangements may reflect the response to risk in a competitive market (Paul). The WH framework provides a test of the null that food producers acquire farm commodities competitively in national markets.

The test recognizes that if firms exert market power in acquiring farm commodities, a gap would exist between the farm price and the industry's demand for farm ingredients. Shifters on the farm supply function would define this gap.

At the level of the firm, the arguments are as follows. Let $P_{fj} = P_{fj}\,(F_j, \boldsymbol{S_j})$ denote the inverse supply function for farm commodities facing the *j*th food industry, where $\boldsymbol{S_j}$ denotes a vector of shifters to this supply function. The first-order condition for profit maximization of a food-producing firm takes the form $MVP = P_{fj} + \lambda f\,(M P_{fj} / MF)$, where *MVP* is the marginal value product or firm-level demand for the farm commodity, and λ is a market power parameter. λ embodies the firm's conjecture about the effect its purchases of farm ingredients will have on the market (Bresnahan, p. 102-104). Note that the term (MP_f / MF) in the above relationship is a function of $\boldsymbol{S_j}$. When $\lambda \quad 0$, the market level demand shifters, $\boldsymbol{S_j}$, enter the firm's optimization rule and define a gap between the market's farm price and the *value of the marginal product* for a competitive firm. Hence, when $\lambda \quad 0$, the marginal farm price – the firm's *MVP* – lies above the average farm price and firms restrict their demand for farm commodities. If $\lambda = 0$ price-taking firms recognize that their purchases impart no effect on the market, the farm price (or the value of the marginal product) equals the *MVP* as the industry level demand shifters ($\boldsymbol{S_j}$,) do not enter firms' optimization conditions.

For a group of non identical firms of an industry, the arguments are similar. By eliminating F_j from equations 1, the two equations reduce to

$$(3) \qquad P_{rj} = B_f^{(j)} P_{fj} + B_w^{(j)} W + B_z^{(j)} Z_j + v_r.$$

Equation 3 is an industry-level relationship similar to the first-order conditions of a price-taking firm. Under the null of no oligopsony power, the vector of supply shifters, $\boldsymbol{S_j}$, does not appear in equation 3. Under the alternative, $\boldsymbol{S_j}$ explains the gap and

$$(4) \qquad P_{rj} = B_f^{(j)} P_{fj} + B_w^{(j)} W + B_z^{(j)} Z_j + \boldsymbol{B_s^{(j)\prime}} \boldsymbol{S_j} + v_r$$

suggests the industry exerts oligopsony power in acquiring farm inputs. Equations 3 and 4 suggest that if industry j acquires farm commodities competitively, $\boldsymbol{B_s^{(j)\prime} = 0}$.

3.0 Structural Change, Cointegration, and Market Clearing

In the previous section, the retail and farm price equations of 1 derive from market-clearing conditions for consumer food products and for farm ingredients. Data and data sources are explained in the Appendix of Reed and Clark (2000). However, questions concerning the specification of equations 1 arise if markets have undergone structural change.

Regardless of the impact of structural change, market clearing means that excess supply (demand) would be of short duration and would equal zero on average. Furthermore, the effects of unforeseen shocks to market clearing would die out over time. In time series jargon, excess supply (demand) would be stationary. It is straightforward to show (e.g. Reed and Clark (2000)) that the error terms, ε_{rj} and ε_{fj} , of equations 1 may represent excess supply (demand) variables for food and farm products. Stationary error terms imply market clearing, and market clearing would prevent the variables of equations 1 from moving too far apart.

In this study we argue that structural change is associated with market trends. Evidence of trends or changes in trends of market variables are often used as indicators of structural change. In time series jargon, variables that are characterized or generated by trends are non-stationary. However, even if each of the variables of equations 1 displays trends, the equations would still reflect market clearing if the excess supply variables or error terms are stationary. If each of the time series variables used in a model display trends and model errors are stationary, the model is *cointegrated* (Engle and Granger). Tests of cointegration are tests of whether the data support the theory. In a cointegrated regression, some mechanism cancels or aligns the trends among the variables and in equations 1 the mechanism is market clearing.

If the trends driving the non-stationary variables of equations 1 are not linked, excess supply would not die out, and the regression would be *spurious* (Granger and Newbold, p. 202-214, Hamilton p. 557-562). If the price equations of (1) are spurious, inter-temporal movements in one set of variables of equations 1 do not explain inter-temporal movements in other variables. A finding of a spurious regression would not support the theory.

In general, if market variables are driven by trends, the trends can be deterministic, stochastic, or a combination of both. A *deterministic* trend is a time trend defined in the usual way. Trends in demographics or predictable increases in real wages and productivity over the last century may drive the deterministic portion of trends in market variables. Market variables generated by deterministic trends pose few problems for statistical inference because with an infinite number of observations, such variables can be forecast from past observations with an arbitrary degree of accuracy. The second type of trend is a *stochastic* trend. Variables driven by stochastic trends are referred to as *unit root* or *integrated* series. For example, trends in real wages tied to unpredictable changes in the direction of inflation, unpredictable changes in the direction of consumer demand, technology, or the continual process of industrial reorganization, may be generating stochastic trends in market variables.[11] Unlike deterministic trends, stochastic trends change direction unpredictably. Integrated market variables pose special problems for statistical inference because even in infinite samples, optimal forecasts of these variables do not converge, but are continually revised as new observations become available.

More formally, the accuracy and reliability of forecasts of market variables depend on whether the variable is driven by a deterministic or a stochastic trend. As the forecast horizon grows, the forecast of a series generated by a deterministic trend converges to a time trend, and the mean squared error (MSE) of this forecast converges to the unconditional variance of the series (Hamilton, p. 438-42). Population, real wages, and real disposable income may be accurately and reliably forecast. On the other hand, tastes and preferences, technology, and the continual reorganization of an industry may be stochastic trends because changes in any of these may be impossible to predict. Unlike deterministically trending variables, the forecast of a unit root variable diverges with the length of the forecast horizon, and the MSE of the forecast increases without bound (Hamilton, p. 438-42).

Associated with each type of trend is a type of cointegration. A model constructed from deterministically trending variable series is *deterministically cointegrated* if the deterministic trends in the model's variables are linked. In practice, a regression model is deterministically cointegrated if a time trend variable appended to the model is not statistically different from zero. A model constructed from a set of stochastically trending series is *stochastically cointegrated* if the model errors are stationary. Just as market variables may reflect both a deterministic and a stochastic trend, a model may be both deterministically and stochastically cointegrated. If a model is cointegrated, then it can be said that the market structure of a model incorporates structural change. Therefore, evidence against cointegration is consistent with structural change within a market that cannot be accommodated by the market structure (that is, in favor of the interpretation that market reorganization is causing a switch to a different market structure).

Using annual time series from 1958-97, Phillips-Perron t-tests for the logged and deflated variables used in the seven sets of retail and farm price equations.[12] Both sets of tests are designed to refute the hypothesis that, conditioned on an AR(1) representation, a single unit root net of an intercept (or drift) or net of a deterministic time trend governs the series. The tests differ in the way they handle serial correlation of the error terms of the AR(1) specification.[13] Almost without exception, the two sets of tests suggest that both a stochastic and a deterministic trend drive most of the variable series used in equations 1.[14]

Given evidence of trends in the variables, the question is whether these equations are stochastically and deterministically cointegrated. The specification of equations 1 used throughout this report is as follows. The deterministic regressors include an intercept and a /deterministic time trend. The stochastic regressors include a vector of (logged) nonfarm input prices ($\boldsymbol{ln\ W}$), a (log) farm supply variable specific to market i ($ln\ Q_i$), and the total demand shifters ($ln\ Z_i$) for each of the consumer demand equations.[15] The vector $\boldsymbol{ln\ W}$ consists of (logs of) wages, the price of packaging, the price of transportation, and the price of energy. To satisfy homogeneity, all prices and income variables in equations 1 and 2 are deflated by the price of other non-farm inputs (Elitzak). Hence, the tests for cointegration are based on a specification that includes six stochastic regressors, a constant, and a deterministic time trend for each retail and farm price equation. We compute two sets of tests. [16]

The first is based on model residuals, and specifically tests the null hypothesis of a spurious regression. Again, a model is spurious (or not *stochastically* cointegrated) if the model errors follow a unit process. Phillips and Ouliaris confirm that the Phillips-Perron statistics can be used to test for spurious regressions. They find, however, that the critical values depend not on the number of observations, but on the number of stochastic regressors used in model specification, and whether the regression includes an intercept or a deterministic time trend.

Table 1 reports Phillips-Perron ‘t’ tests designed to refute the null that the equations 1 are spurious regressions. The statistics are based on Ordinary Least Squares (OLS) residuals. The Phillips-Perron results fail to reject the null for 8 of the 14 equations. However, it is difficult to conclude that cointegration exists using the Phillips-Perron tests at usual significance levels because the null hypothesis is “no-cointegration”. Indeed, Johansen and Juselius (1990) argue that wider significance levels be used when testing for the null of no cointegration because the tests are likely to have low power for finding cointegrating vectors with roots close to the unit circle.

The second set of tests is designed to examine the null that the regressions are stochastically cointegrated. The tests are based on the observation by Park (1990) that appending a set of integrated series to a stochastically cointegrated model yields a spurious regression. If the additional variables add no explanatory power to the regression, they are superfluous, and the original model specification is cointegrated. The technical problem of testing whether the variables are superfluous is that, in general, the model error terms are correlated with the first differences of the model’s regressors. This correlation destroys the asymptotic normality of parameter estimates, and hence destroys the reliability of the usual chi-square tests. Park (1990) derives a transformation that accounts for this correlation, and uses it to transform each of the variables of a model. Chi-square tests based on the transformed regression represent valid tests of the null that the additional variables are superfluous, and the original model is stochastically cointegrated.

To employ the test, however, one is faced with choosing a set of integrated and potentially superfluous variables to append to model. Here, theory provides no clear guide. Hence, we follow Park's suggestion by appending higher order polynomials of deterministic time trends to the retail and farm price equations.

Table 2 reports chi-square estimates associated with Park=s J_1 test (1990) of the null that the coefficients of the polynomial time trend terms (T^2, T^3 & T^4) are jointly zero (see table 2 for the specification of the polynomial terms). The p-values (in parentheses) suggest that at the 0.05 level of rejection, all equations are stochastically cointegrated except the retail price equation for poultry and the farm price equations for beef, poultry, and dairy.

The results in tables 1 and 2 provide somewhat mixed results. The Phillips-Perron tests suggest that, at reasonable levels of rejection, 8 of the 14 price equations are cointegrated. Finally, Park's J_1 test suggests that, at reasonable levels of rejection, 10 of the 14 equations are cointegrated. In combination, the Phillips-Perron and Park's test results suggest that only the retail price equation for poultry and the farm price equation for beef and veal may be spurious. In the next section we estimate all relationships as cointegrated relationships aware of potential problems with these two equations.

Further Empirical Results

In the previous section, we argued that trends in market data reflect structural change, and found evidence of both deterministic and stochastic trends in key variables associated with seven U.S. markets. In addition, we found evidence that markets distribute these trends across consumers and food producers. Despite the claim that food markets may have undergone a sequence of permanent changes over time, we show in this section that market-clearing provides stable long-run retail and farm price relationships.

The stochastic trends embedded in the variables of equations 1 require us to deviate from textbook estimation procedures. As stated above, such procedures fail to account for a non-zero correlation (at any lag) between the first difference of an explanatory variable (i.e., the fundamental error terms of the variables) and a cointegrated model's stationary error terms. This correlation is present in all but the simplest class of cointegrated models. While it does not destroy the consistency of parameter estimates, the correlation does destroy the asymptotic normality of the estimates and renders textbook formulas for the χ^2, F, and t tests invalid for inference.

Park (1990, 1992) and Park and Ogaki transform variables of cointegrated regressions based on this correlation. Their transformations reduce general, cointegrated regressions to the simple (or canonical) class of cointegrated regressions in which first differences of explanatory variables are *not* correlated with regression errors. The procedure is to first transform the variables of a cointegrated regression and then to apply textbook procedures to the transformed regressions. The canonical cointegrating regression (CCR) estimator applies OLS to a transformed single equation (Park 1990). We used the CCR estimator in the previous section to compute Park's variable addition test of the null of cointegration (Park 1992). In this section we again use the CCR estimator to compute a variable addition test of oligopsony power. In addition, we apply the seemingly unrelated regression (SUR) estimator to a transformed, seven-equation consumer demand system, and to the cointegrated quasi-reduced-form retail and farm price equations (i.e., equations 1) for each industry. This two-step estimator, termed the seemingly unrelated canonical cointegrating regression estimator (SUCCR), provides us with unbiased estimates of market structure and asymptotically-correct inference on tests of market power and constant returns in multiple equation systems (Park and Ogaki). We refer interested readers to Park, and to Park and Ogaki for details on the transformations that we use to compute the estimates presented in this section.

Consumer Demand

Kinsey and Senauer argue that changing trends in consumer behavior lead to a changing structure of the food sector. Cointegrated, market-clearing relationships would reflect the transmission of trends from consumers. To capture trends in consumer demand, we specify and estimate a consumer demand system for the seven industries. In this section, we discuss the specification of the seven-equation consumer demand system.

To construct the empirical consumer demand model, we used logged data on per-capita consumer disappearance as proxies for the seven dependent per capita consumption variables, and deflated all prices and income (explanatory variables) by the price of other nonfarm inputs (to ensure homogeneity of the market clearing conditions). Details of the construction of these variables are given in Reed and Clark (2000). The restricted estimates were then used to construct the demand shifters, $ln\ Z_j$, for each industry j (equation 2).[17]

Tests of Competition and Constant Returns

Table 3 reports the χ^2 and p-values associated with symmetry, constant returns or zero profits for the industry, and the joint restrictions of symmetry and constant returns for the seven industries. Failure to refute symmetry suggests food firms take both output and farm ingredient prices as given. Failure to reject constant returns for the *industry* suggests that free entry and exit of diverse firms result in zero long run profits. Failure to refute the joint hypotheses of symmetry and constant returns suggest that in the long run, a 1-percent increase in the price of a farm commodity results in an increase in the price of a composite food category by a percentage equal to the cost share of the farm commodity used in producing the food category.

The symmetry (only) and constant returns (only) test results provide evidence of long run competition. In particular, the symmetry test fails to refute (at the 0.05 level) the long run competitive model for the beef, dairy, eggs, fresh fruit, and fresh vegetable industries. The constant returns test fails to refute the long run competitive model for poultry, fresh fruit, and fresh vegetables. It is worth repeating that this general finding of competitive markets takes into account the many permanent changes that may have occurred in these markets over time.

Furthermore, our tests reject the joint restriction of symmetry and constant returns for all industries except fresh fruit and fresh vegetables. The results suggest that estimates of elasticities of farm price transmission to retail apply only to markets in which final products undergo a minimal amount of food processing.

The general finding of competitive markets is consistent with WH and Wohlgenant's (1989, 1994, 1996) findings. On the one hand, we expect our findings to be similar because the model structures and data are very much the same.[18] On the other hand we expect differences because of the different estimation procedures. While our approach exploits deterministic and stochastic trends in market data, the cited works remove stochastic trends through a first-difference transformation prior to estimation. In comparing the procedures using the same retail and farm price equations, Reed and Clark (1999) find that one fails to reject parametric restrictions more often using a first-difference specification of an econometric model.[19] The reason is if the explanatory variables are integrated, a first-difference transformation removes the dominant, longrun component of the variance of the variables. Hence, if the variables are integrated, a first- difference filter would inflate the variance of parameter estimates and could reduce the likelihood of rejecting *any* parametric restrictions. It is noteworthy that we reject both the symmetry and the joint restriction of symmetry and constant returns more often than the cited works.

Oligopsony Power

In a previous section, we reviewed the theory used to test for oligopsony power. If food firms exert oligopsony power in acquiring farm ingredients, a gap would exist between the farm price and the value of the marginal product of farm ingredients at the market level. Shifters on the farm supply associated with the *j*th market, $\boldsymbol{S_j}$, would explain this gap. Recall from above that under the null hypothesis of food producers taking farm prices as given, no gap exists and the retail-farm price relationship is

$$P_{rj} = B_f^{(j)} P_{fj} + B_w^{(j)} \boldsymbol{W} + B_z^{(j)} Z_j + v_r. \tag{3'}$$

Under the alternative of oligopsony power, the retail-farm price relationship is

$$P_{rj} = B_f^{(j)} P_{fj} + B_w^{(j)} \boldsymbol{W} + B_z^{(j)} Z_j + \boldsymbol{B_s^{(j)\prime}} \boldsymbol{S_j} + v_r. \tag{4'}$$

A test of whether firms acquire farm commodities competitively in national markets reduces to a test of the restriction $\boldsymbol{B_s^{(j)\prime} = 0}$.

The usual chi-square tests of statistical significance of the $\boldsymbol{S_j}$ variables would be reliable only if the variables of equation *3'* and the $\boldsymbol{S_j}$ would be stationary. Because we found evidence that both sets of variables are integrated, we proceed as follows. Under the null hypothesis of price-taking, equation *3'* is cointegrated and its error terms are stationary, and the variables of equation *3'* are transformed to account for the correlation between first differences of explanatory variables and the model error terms (Park 1990, 1992). Under the null, the integrated (untransformed) $\boldsymbol{S_j}$ variables would be independent of the stationary error terms of equation *3'*, and $\boldsymbol{B_s^{(j)\prime} = 0}$. Under the alternative of oligopsony power, the error terms of equation *3*' would be integrated, and this price-taking relationship would be spurious. In this case, the integrated $\boldsymbol{S_j}$ variables and the integrated error terms of equation 3 would not be independent and in general $\boldsymbol{B_s^{(j)\prime} \neq 0}$. Rather than testing for the statistical significance of $\boldsymbol{S_j}$ **,** chi-square tests of $\boldsymbol{B_s^{(j)\prime} = 0}$ represent a test of whether the price taking model is cointegrated or correctly specified against the alternative that the oligopsony power relationship is correctly specified (Park 1992).

Table 4 reports the chi-square and p-values computed from the transformed regressions. The results report the statistics associated with one integrated, industry-specific farm supply shifter (S_1) and both integrated, industry-specific farm supply shifters (S_1 & S_2).[20] The results are based on a specification that includes a constant and a deterministic time trend. At reasonable levels of rejection, we fail to reject the null that in national markets, the seven food industries acquire farm ingredients competitively.

Long Run Industry Structure

Table 5 presents SUCCR estimates of the parameters of equations 1 for the seven food markets.

Although they account for a negative own-price consumer response, they are conditioned on shifters of consumer demand (i.e., *lnZ*). Hence, the estimates would not account for particular shifts in consumer demand induced by endogenous changes in relative retail prices among the seven composite markets. However, by controlling for such shifts, the 'quasi' reduced-form estimates of equations 1 provide information on industry structure. Given evidence of permanent change and cointegration presented above, the results in table 5 represent long-run estimates of industry structure.

Theory predicts a negatively sloped, long run industry demand for farm ingredients. In terms of equations 1, theory predicts $A_{ff} < 0$. The negative estimates of A_{ff} for each of the seven markets are statistically different from zero. The estimates describe downward sloping, industry-level demand schedules for farm ingredients.

The theory of diverse firms in a competitive market predicts that positive shifts in the consumer demand function trace an upward sloping, long run industry supply schedule. In terms of equations 1, theory predicts $A_{rz} > 0$. The estimates of A_{rz} are positive for all seven markets, and except for fresh fruit and fresh vegetables, they are statistically different from zero at reasonable levels of rejection.

The theory of competitive markets predicts that if farm ingredients are normal factors of production, a contraction in farm supply raises consumer food prices. In terms of equations 1, theory predicts $A_{rf} < 0$. The estimates of A_{rf} are negative for each of the seven industries, and are statistically different from zero. Theory also predicts that if farm ingredients are normal, $A_{fz} > 0$. The estimates of A_{fz} are positive for all seven markets and are statistically different from zero. Negative estimates of A_{rf} and positive estimates of A_{fz} suggest the aggregate farm ingredients are normal factors of industry production.

The estimates presented in table 5 suggest some marketing factors are inferior to a number of industries. Negative signs on elements of $\boldsymbol{A}_{rw}$ suggest the particular factor is inferior and that the supply response of inframarginal firms exceeds that of marginal firms. For example, the results suggest transportation is an inferior factor for the beef and pork industries. The estimates may indicate that for the U.S. pork industry, changes in vertical coordination have allowed the inframarginal firms in the Southeast United States to economize on the transportation of hogs. The estimates also suggest that labor is an inferior factor for the fresh fruit and fresh vegetable industries.

The results presented in table 5 also point to some nonfarm inputs that appear to be normal across industries. The positive signs on the A_{rw} coefficients associated with the price of packaging suggest that packaging is a normal factor for all seven industries. This may reflect the notion that consumers value the convenience associated with the packaging of food products, and suggests that consumers would be willing to pay more for packaging through higher food prices. Furthermore, labor appears to be a normal factor of production for four of the seven industries.

Conclusions

In this study we present a theoretical model and statistical framework for testing for market power in the US agri-food industry. Our theoretical model is designed to maintain as few hypotheses as possible before undertaking empirical analysis. Furthermore we explicitly deal with the issue of structural change as one where variables are driven by stochastic or deterministic trends. In this sense, our procedures are more general in their application and interpretation than those proposed in the past. The series of tests used is an extensive one, ranging from parametric restrictions placed on a generally specified model to cointegration tests of individual equations.

In general, our results tend to confirm a greater degree of competition in aggregate US agri-food industries than have been found in the past. Certainly, there is no universal overall trend in increasing market power revealed by our test results in the data. Past studies that find general evidence in favor of market power could be due to the rejection of maintained hypotheses rather than tests for market power. Perhaps more general methods of theoretical development or empirical techniques need to be developed in order to draw sharper conclusions from the data. Specifically, our tests of market power rely heavily on asymptotic results the in development of test statistics. There is growing evidence that the use of asymptotic results to develop critical values used in test statistics may seriously bias tests against acceptance at usual levels of significance (Ng, (1995) and Clark and Grant (2000)). Certainly more work needs to be done on these and other issues before general statements concerning market power in the US agri-food industry can be made.

Endnotes

[1] Wohlgenant (1999) formally shows that if one analyzes a competitive industry producing a heterogeneous mix of final consumer goods that we treat as a single composite (e.g., beef), the *observation* that retail-to-farm price spreads widen with increases in consumer food prices (e.g., George and King) implies input substitution. To explain this observation with a fixed-proportions based model for this heterogeneous industry one must *rule out* the competitive model.

[2] Retail-to-farm price spreads used by ERS/USDA (Elitzak) are based on fixed-proportions production. Formulas based on variable-proportions would yield different magnitudes.

[3] These results are predicted by the theoretical results presented in Wohlgenant (1999).

[4] A brief discussion of the relationship between the structural model and the quasi-reduced form is provided in Appendix A. The reader is referred to Wohlgenant (1989) or Wohlgenant and Haidacher for a more complete discussion.

[5] Constants and deterministic time trends are added to all of the empirical specifications below except the system of consumer demand relationships (Reed and Clark (2000)). Only a constant term was added to the consumer demand system.

[6] The quasi-reduced-form equations derive from Heiner's seminal work and the extensions of this work by Wohlgenant (1989) and WH. In the quasi-reduced-form representation, shifts in the market's demand schedule are exogenous.

[7] For any single firm, Heiner found that the simultaneous change in the output price caused by the change in input price may trace out a *positively* sloped input demand for the firm. He found this positive relationship disappears when summing over all firms.

[8] Correspondingly, the retail price equation of (1) is a Heiner-type of industry-level output supply schedule.

[9] The example given here would not hold for the special case of only two inputs (e.g., one farm and one non-farm input). In this two input case both factors must be normal, and increases in the price of either input raise the output price.

[10] Because firm-level production functions are not identical, a factor of production can be normal for some firms and inferior for others (e.g., older versus modern plants). Hence, a factor is normal (inferior) for an *industry* if the industry uses more (less) of the factor as it increases output. The weighted sums of individual firm-level elasticities determine whether a factor is normal or inferior.

[11] That is, a series that is stationary around a deterministic trend.

[12] The sample series used to create the variables are discussed in the Appendix. All price and

income variables are deflated by the price of other nonfarm inputs and logged prior to testing. The total demand shifters are computed directly from the estimates of the double-log level system of consumer demand equations. Prices and income are also deflated by the price of other nonfarm inputs prior to estimation. The test results were computed using Shazam.

[13] Phillips and Perron compute estimates of the covariogram of the errors of an AR(1) process. For a concise comparison between the tests we refer the reader to Hamilton (p. 504-518). The simulations presented in Phillips and Perron (1988) reveal that neither test is universally more powerful than the other.

[14] The Phillips-Perron results are available upon request. Some results conflict. For example, the results suggest the farm prices for poultry and eggs may be stationary around a time trend (-3.95 and -4.49) but are unit root non-stationary around an intercept. The results also suggest the farm supply for beef may be stationary around a constant but non-stationary around a time trend. When unit root tests conflict, Holden and Perman spell out a multi-step procedure that may be useful in sorting out the results.

[15] The seven-equation demand system was also found to be stochastically cointegrated, and seemingly unrelated canonical cointegrating regression estimates with an intercept and no time trend and symmetry and homogeneity imposed are used to construct the demand shift variables used in equations 1.

[16] Because we found that a linear deterministic time trend variable was invariably statistically different from zero, we reject the null of deterministic cointegration for each price equation and included it in the model specifications for each industry. Hence, our tests of cointegration are tests specifically for stochastic cointegration.

[17] We are aware of the problem with incorporating the adding-up condition on this double-log specification (Deaton and Muellbauer, p. 17), and are aware of the conceptual problem of using farm-level disappearance data as the dependent variable of the system (WH). Our purpose here is to compute only approximate values of the shifters on consumer demand.

[18] We are aware that the model specifications for eight industries in Wohlgenant (1989, 1994) include only a single nonfarm input price. The model specification for beef and pork (only) used in his 1996 paper is similar to the specification used here, as it includes the same four nonfarm input prices. Furthermore, our work uses a different deflator to impose homogeneity.

[19] The study controls for differences in the data and model specifications.

[20] For the test to be meaningful, the variables must be integrated. We could not refute the claim of integrated farm supply shifters. Furthermore, because the null hypothesis is that equation *3'* (and not equation *4'*) is cointegrated, the $\boldsymbol{S_j}$ variables are not transformed.

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Table 1 – Phillips-Perron Residual-based tests of spurious regressions

Retail Price Equations		
Beef and veal	-5.73**	(1)
Pork	-5.74**	(3)
Poultry	-4.44	(1)
Eggs	-3.80	(1)
Dairy	-7.52**	(1)
Fresh fruit	-4.12	(1)
Fresh vegetables	-4.55	(2)
Farm Prices (*ln* P_f)		
Beef and veal	-3.15	(1)
Pork	-3.49	(1)
Poultry	-5.21*	(1)
Eggs	-4.99	(1)
Dairy	-6.00**	(1)
Fresh fruit	-3.92	(1)
Fresh vegetables	-5.23*	(1)

Values are t-tests associated with the coefficient of the lagged OLS residuals in which the regression includes a constant and a time trend. Values in parentheses indicate the number of lags included in the error covariogram.

*Reject the null of a spurious regression at (approximately) the 0.10 level. The result is based on a critical value of approximately -5.2. which is -0.5 plus -4.7. -4.7 is the critical value computed by Phillips and Ouliaris for a demeaned (constant) and detrended (one deterministic time trend) regression with five stochastic regressors (Phillips and Ouliaris, Table IIc). -0.5 is the increment associated with adding the sixth stochastic regressor (Ng).

**Reject the null of a spurious regression at (approximately) the 0.05 level. The result is based on a critical value of approximately -5.5 which is -0.5 plus -5.0. -5.0 is the critical value associated with a demeaned and detrended regression with five stochastic regressors and -0.5 is the increment associated with the sixth regressor (Ng).

Table 2 – Variable-addition tests of cointegration

Industry	Retail price equations	Farm price equations
Beef and veal	6.83 (.08)	9.52 (.02)
Pork	3.75 (.29)	0.59 (.90)
Poultry	18.23 (.00)	27.27 (.00)
Eggs	4.81 (.19)	3.16 (.37)
Dairy	7.72 (.05)	16.90 (.00)
Fresh fruit	1.28 (.73)	6.83 (.08)
Fresh vegetables	0.31 (.96)	2.92 (.40)

Entries are χ^2 values associated with the restriction $\alpha_1 = \alpha_2 = \alpha_3 = 0$ in the general regression $P = \mathbf{X\beta} + \mathbf{f(\alpha,T)} + e$ in which $\mathbf{f(\alpha,T)} = \alpha_1 T^2 + \alpha_2 T^3 + \alpha_3 T^4$ and in which $T = t/\max(t)$ where P is either the logged and deflated retail or farm price, X includes the intercept, the linear time trend, and the six logged and deflated stochastic regressors. The values in parentheses are p-values, and represent the size of the rejection region associated with the restriction. For example, values greater than 0.05 fail to reject the null of stochastic cointegration at the 0.05 level of rejection.

Table 3 -- Tests of symmetry and constant returns

	Symmetry only	Constant returns only	Symmetry & constant returns
Beef and veal	0.4773	87.9159	97.2574
	(.490)	(0.00)	(.000)
Pork	94.9740	34.3050	98.0828
	(.000)	(0.00)	(.000)
Poultry	26.1533	4.0383	39.4573
	(3E-7)	(.133)	(1E-8)
Eggs	0.0381	223.52	255.7759
	(.845)	(0.00)	(0.00)
Dairy	0.9081	48.6256	49.1519
	(.341)	(0.00)	(.000)
Fresh fruit	2.1428	4.7536	4.7871
	(.143)	(.093)	(.188)
Fresh vegetables	1.7731	0.8505	6.0862
	(.183)	(.654)	(.107)

Values are chi-square statistics. Values in parentheses are p-values, or the size of the rejection region necessary to reject the null hypothesis.

Table 4 -- Tests of competition in acquiring farm commodities

	S_1	S_1 & S_2
Beef and veal	1.2377 (.266)	1.3832 (.501)
Pork	0.0443 (.833)	2.4686 (.291)
Poultry	0.0538 (.816)	0.2956 (.862)
Eggs**	0.1994 (.655)	
Dairy	0.1294 (.719)	0.2022 (.904)
Fresh fruit	2.5509 (.110)	
Fresh vegetables	0.2176 (.641)	

Entries are χ^2 values and values in parentheses are significance levels. The sets of supply shifters on farm supply are as follows (see Appendix for data series definitions): Beef: S_1 is steers, S_1 & S_2 are steers and corn price; Pork: S_1 is hog inventories, S_1 & S_2 are hog inventories and corn price; Poultry: S_1 is the price of soybean meal, S_1 & S_2 are the price of soybean meal and corn price; Eggs: S_1 is laying flock; Dairy: S_1 is cow numbers and S_1 & S_2 are cow numbers and price of soybean meal; Fresh fruit: S_1 is farm wage; Fresh vegetables: S_1 is farm wages.

**Sample interval is 1960-97.